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AN ENGINEERING SCALE MODEL FOR PREDICTING THE SHORELINE RESPONSE TO VARIATIONS IN WAVES AND WATER LEVELS

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ABSTRACT

An alternative approach for simulating shoreline changes due to variations in waves and water levels over the timescales of engineering relevance has been developed, calibrated and evaluated using historical shoreline data from 13 sites within the United States and Australia. The **E**ngineering **S**cale Shore**l**ine **Mod**el (ESlMod), is an equilibrium based model in which the shoreline continuously evolves towards an equilibrium position determined by the dynamic local conditions. The rate at which the equilibrium position is approached is a function of the degree of disequilibrium and a coefficient which can either be treated as a calibration constant or parameterized in terms of the local conditions. Both approaches are considered here. Initial results are positive, as an overall average normalized mean square error of 0.653 has been calculated for the over two thousand simulations performed thus far.

1. INTRODUCTION

The objectives of the present work can be divided into a set of long-range and short term goals. The long range goal is to develop a robust model, capable of simulating shoreline changes due to both longshore and cross-shore processes over a variety of timescales ranging from those associated with individual storm events up to several decades. Such a model could be used to generate real-time forecasts based on observed data, or in a short term forecast mode applied in concert with hydrodynamic models. Long-term predictions would also be possible using Monte Carlo techniques and known distributions of select forcing parameters. In either mode, anthropogenic factors could easily be incorporated into the simulations.

Unfortunately, traditional modeling approaches have failed to yield a single model capable of being applied to these different scenarios. There are numerous reasons why such a model has yet to be developed, not the least of which is the extraordinary complexity of the problem. The most common approach has been to treat the longshore and cross-shore components of the problem separately in an effort to simplify the problem. Simple yet fairly robust solutions for calculating the shoreline change due to gradients in the longshore transport have been developed (Larson, et al.,

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1997); however these solutions typically neglect cross-shore processes which can be significantly more important especially on long straight coastlines.

The short-term objective, which is the focus of this paper is to develop a simple cross-shore model which ultimately may be applied in conjunction with existing one-line models, such that both the longshore and cross-shore processes are represented in one relatively simple, yet fairly robust numerical model. Such a model would theoretically be applicable over both longer timescales where the gradients in longshore transport are expected to be dominant, as well as over shorter time scales, where seasonal and/or storm related changes are expected to be more significant. The key to developing such a model lies in preserving the simplicity inherent to one-line models, while also providing a physically based backbone, such that the simulations have a sound (albeit simplified) theoretical basis. The model discussed here falls into this category, where an alternative approach to modeling shoreline changes has been taken. A series of laboratory and numerical observations were used to guide the development of a simplified model for representing shoreline changes over a variety of time scales due to variations in waves and water levels. The initial evaluation of the model at thirteen sites within the U.S. and Australia indicates that the model exhibits significant promise, and that coupling it with a one-line model should be possible in the future.

2. MODEL DESCRIPTION

The **E**ngineering **S**cale Shore**l**ine **Mod**el (ESlMod) was developed by Miller and Dean (2004) (referred to hereafter as MD04) as an alternative means of simulating shoreline changes due to variations in waves and water levels over the timescales of engineering interest. The model is based upon both small (Swart, 1974) and large scale (as reported in Dette and Uliczka, 1987; Sunamura and Maruyama, 1987; and Larson and Kraus, 1989) laboratory observations, as well as previous numerical simulations (Kriebel and Dean, 1985; Larson and Kraus, 1989), which have shown that a shoreline acted upon by a combination of waves and elevated water levels evolves towards an equilibrium position with an approximately exponential time scale. This suggests that it might be possible to model the shoreline change using a heuristically based, simple equilibrium equation

$$\frac{dy(t)}{dt} = k_\alpha \left(y_{eq}(t) - y(t) \right) \quad (1)$$

where y(t) is the actual shoreline position, $y_{eq}(t)$ is the equilibrium shoreline position, and k_α is a rate coefficient. Models of this form have been used in the past to successfully describe beach state transitions (Wright et al., 1985), bar migration (Plant et al., 1999), beach slope variability (Madsen and Plant, 2001), and even shoreline changes (Kriebel and Dean, 1993); however the previous attempt to apply eq. 1 to shoreline changes adopted an analytical approach for which solutions were only obtainable for a limited number of idealized forcing functions. The numerical technique described in MD04 offers the advantage that an unlimited number of more realistic forcing conditions can be considered.

The key components of eq. 1 are the equilibrium shoreline position and the rate coefficient, both of which must be adequately defined in order for a realistic and meaningful solution to be obtained. The equilibrium shoreline position is defined using a modified version of the Bruun Rule (1962) which includes the effects of wave setup. A definition sketch is provided in Figure 1, where the total water level varies across profile, as the wave setup $\zeta(y)$ increases between the breakpoint and the shoreline. Assuming sediment volume is conserved during the transition from the initial to the final profile, equilibrium beach profile methodology can be used to show that the resulting shoreline recession for the conditions of Figure 1 is given by

$$\Delta y_{eq}(t) = -W_*(t)\left(\frac{0.068H_b(t)+S(t)}{B+1.28H_b(t)}\right) \quad (2)$$

where H_b is the breaking wave height, S is the traditional storm surge (here the spatially constant water level increase), B the berm height, and W_* the width of the active surfzone. In the present analysis, W_* is defined as the distance to the breakpoint, such that W_* can be parameterized in terms of the breaking wave height. Eq. 2 defines an equilibrium shoreline change, as it is assumed that the conditions shown in Figure 1 persist long enough for the profile to fully adjust. In nature, equilibrium may never be reached, as the profile continuously adjusts in response to the dynamic nearshore conditions. If the baseline condition is known, the equilibrium shoreline changes given by eq. 2 can be converted to equilibrium shoreline positions according to

$$y_{eq}(t) = \Delta y_o + \Delta y_{eq}(t) \quad (3)$$

Since in general, the relationship between the baseline condition for eq. 2 and the baseline of the shoreline measurements is not known, Δy_o is determined through calibration.

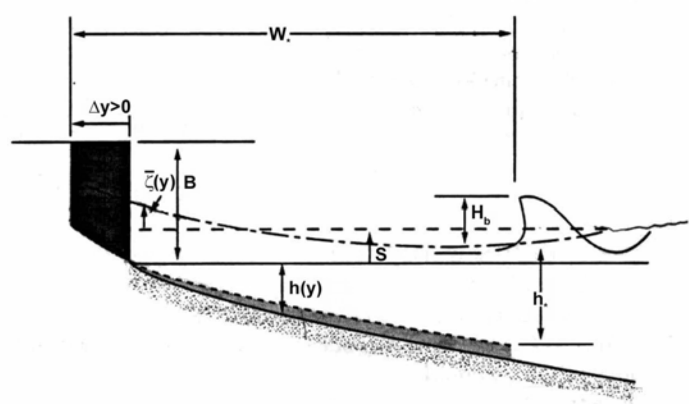

Figure 1 Definition sketch for calculating shoreline recession due to a combination of a uniform water level increase, S, and a cross-shore varying wave induced setup ζ(y).

The constant of proportionality in eq. 1, k_α, is a rate term, which may be treated as a calibration coefficient or parameterized in terms of the local conditions. Both approaches are considered here, where in the simplest case k_α is taken as a double valued constant to be determined through calibration, with one value applying to accretion (k_a) and another to erosion (k_e). A slightly more realistic approach is to assume that the rate coefficient can be parameterized in terms of the nearshore conditions. This method has the advantage that the rate coefficient is allowed to vary with time, so that for example during a strong storm the value of k_e might be significantly larger than during a smaller storm. Although an infinite number of possible parameterizations exist, those considered here, have an inherent and well-documented physical basis. A total of 15 possible parameterizations (see Table 1 for a complete list) were considered, where the forms of the erosion and accretion parameters were considered independent of one another. In all cases the complete rate parameter is given by, $k_\alpha(t)=k_\alpha X(t)/X_{norm}$, where k_α is an empirically determined coefficient, X(t) is the parameterization function, and X_{norm} is a specific value of X(t) which normalizes the parameter.

In some cases the value of X_{norm} is based upon some previously determined critical value of that parameter (i.e. P = 26,500, the value of the profile parameter which separates barred and unbarred profiles for field data), while in other cases it represents the value of the parameter for average wave conditions.

Compared to previous generations of the model, the present version of ESlMod contains several improvements designed to more realistically represent some of the physical processes involved. By far the most significant improvements relate to the addition of several new rate coefficient parameterizations and the incorporation of the inverse forms of each parameter. Including the inverses was motivated by the initial results which showed that k_a was most effectively parameterized by the surfzone Froude number, which at the time was the only parameterization inversely proportional to the wave height. Slight changes were also made to the way in which y_{eq} was calculated. The active surfzone width, W*, was modified throughout to incorporate the results of Wang (2004) who showed that the sediment scale parameter (A in the equilibrium beach profile relationship $h = Ay^{2/3}$) varies with non-dimensional fall velocity parameter. For calm conditions, the impact is negligible; however for steep waves and storm conditions, the width of the active surfzone is stretched significantly as the profile becomes more dissipative. Another modification involves the inclusion of a non-traditional, time-varying beach slope based on the relationship between W_* and h_* (here equivalent to h_b). Since no consensus exists on exactly how or where to measure the beach slope, the time varying beach slope was defined as $m(t)= h_*(t)/W_*(t)$. Other modifications which are not discussed in detail here include several improvements to the calibration and computational routines designed to increase the efficiency of the model.

Table 1 Parameterizations considered for k_α.

Parameter	Description
Con	Calibration constant
Ω & Ω^{-1}	Non-dimensional fall velocity parameter (& inverse)
H_b^2 & $(H_b^2)^{-1}$	Proportional to wave energy (& inverse)
$H_b^{2.5}$ & $(H_b^{2.5})^{-1}$	Proportional to wave energy flux (& inverse)
F_r & F_r^{-1}	Surfzone Froude number (& inverse)
ζ & ζ^{-1}	Surf similarity parameter (& inverse)
P & P^{-1}	Profile parameter (& inverse)
H_o/L_o & $(H_o/L_o)^{-1}$	Wave steepness (& inverse)

3. METHODOLOGY

ESlMod has been calibrated and evaluated at a total of 13 sites in both the United States and Australia as shown in Figure 2. The three sites which are discussed in detail in this paper: Long Beach, WA, Torrey Pines, CA, and Wildwood, NJ are capitalized and italicized in the figure. Prior to applying the model, each shoreline data set is longshore averaged and detrended. The longshore averaging is done to obtain a more representative shoreline and remove small scale spatial variations in the data. The long-term trends are removed as it is assumed they are caused by gradients in the longshore sediment transport, not the cross-shore processes included in the model. Once ESlMod is coupled to an appropriate longshore model, this pre-processing step will be eliminated.

At each site, a total of 225 model runs were performed, representing all possible combinations of the rate parameters. This results in a 15 by 15 matrix of simulations, each with its own set of calibration coefficients, and shoreline predictions. The normalized mean square error (NMSE) is used as the primary criteria for both calibrating and evaluating the model. The NMSE is defined as

$$\mathrm{NMSE} = \frac{\sum_t \left(y_{pr} - y_{ob}\right)^2}{\sum_t y_{ob}^2} \tag{4}$$

where y_{pr} are the predicted values and y_{ob} are measured or observed shoreline positions. During the calibration, the NMSE between the model predictions and historical shoreline measurements is minimized using an iterative procedure. In addition to the NMSE, each simulation is assigned a CAP score which essentially measures the effectiveness of the model in predicting the correct direction (erosion, accretion, stable) of shoreline change. The details of the CAP calculation will not be discussed here; however a CAP score of one represents a perfect simulation (i.e. all observed changes are classified correctly by the model although the magnitude of the change may be incorrect), while a score of zero indicates that the model incorrectly classifies all the measurements.

Shoreline and forcing data for the calibration and evaluation routines were obtained from a variety of sources. Typically the shoreline changes used here were obtained from more detailed profile measurements, although in some cases aerial photographs were used to supplement the analysis. The wave and water level data required to force the model are readily available from a number of sources. Typically the water level data are obtained from the database of water level records maintained by the National Oceanic and Atmospheric Administration (NOAA) Center for Operational Oceanographic Products and Services (CO-OPS). Measured wave data for many of the U.S. sites is available from the NOAA National Data Buoy Center (NDBC). Due to the distance of many of these gauges from the sites however, nearshore wave data from local sources was used wherever possible.

The shoreline data collected at Long Beach, WA represents only a small subset of a much larger data set collected by the United States Geological Survey, and the Washington State Department of Ecology as a part of an in-depth study of the Columbia River Littoral Cell (Kaminsky et al., 1998; Ruggierro et al., 1999; Ruggierro and Voigt 2000; Ruggierro et al., 2005). Typically the shoreline data are collected quarterly. Forcing data for the site is provided by the combination of a NOAA tide gauge located near the mouth of Willapa Bay (ID #9440910), and two wave gauges (Scripps CDIP-036, NDBC 46029) located just offshore.

The Torrey Pines shoreline data were extracted from one of the earliest sets of complete (onshore & offshore to depths of over 60 ft) profile data collected in the U.S. (Nordstrom and Inman, 1975). Due to the fact that the profile data extend sufficiently far offshore, an adjustment can be used to remove the portion of the shoreline change associated with the difference in the total sediment volume between surveys and potentially related to gradients in the longshore sediment transport. The adjustment assumes any advancement (recession) due to a gain (loss) in sediment volume between surveys is evenly distributed between the berm and depth of closure. Water level information for the site was taken from the NOAA tide gauges located in San Diego (ID #9410230) and Los Angeles (ID #9410660). The local gauge was used preferentially; however during spot outages an adjusted version of the Los Angeles data was used to complete the record. Wave measurements during the period of record (1972-1974) are sparse, therefore it was necessary to use statistical hindcasts (WIS SC002) created by the U.S. Army Corps of Engineers in place of measured data.

The shoreline data for Wildwood, NJ were collected by Richard Stockton College as a part of the state sponsored New Jersey Beach Profile Network (Farrell et al., 2003; Farrell et al., 2005). These semiannual profiles only extend to wading depth; therefore a shoreline adjustment similar to that described in the previous paragraph was not used. Wave data for the site was obtained from a combination of the nearest deep-water NDBC buoy (44009) and a nearshore gauge (NJCMN-Avalon) maintained by Stevens Institute of Technology (Herrington et al., 2000). When both wave data sources are available, priority is given to the nearshore gauge as it more closely reflects the wave climate at the site. Several sources of water level data were used. Primary water levels were obtained from the Stevens gauge at Avalon, with back up data provided by NOAA water level stations in Atlantic City (ID #8534720) and Cape May (ID # 8536110).

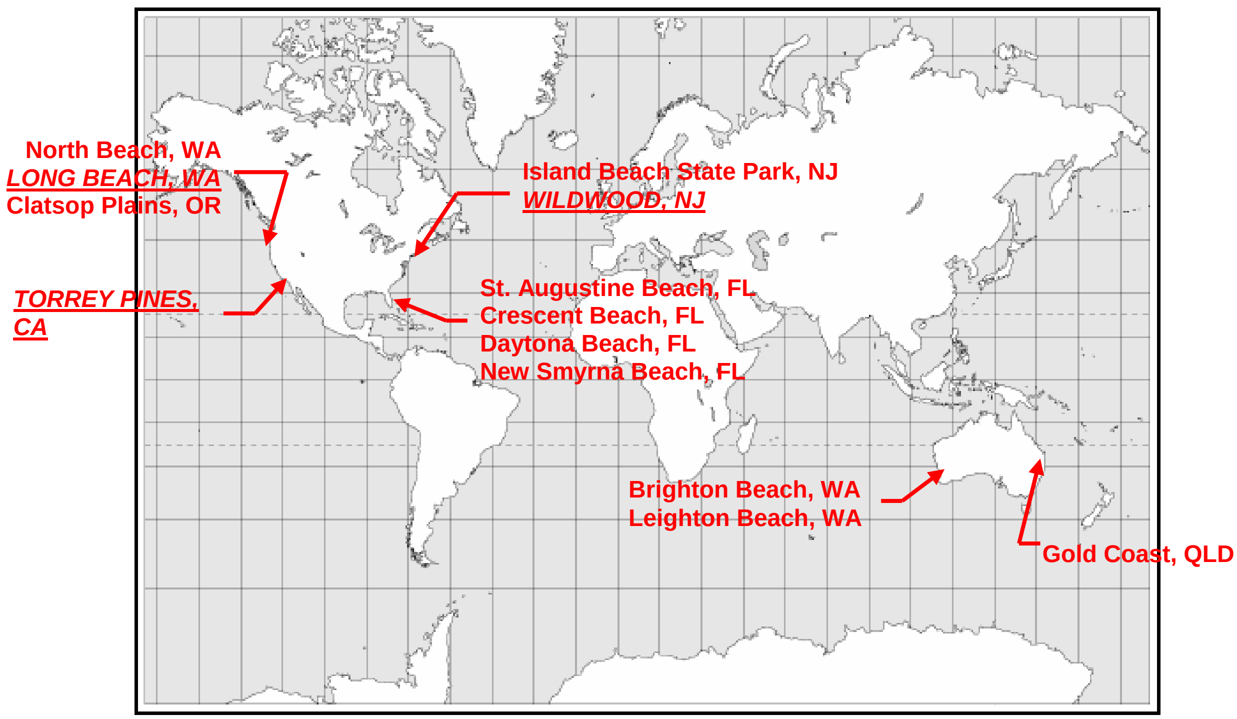

Figure 2 Site location map. Locations discussed in detail are italicized and underlined.

4. RESULTS

A typical simulation representing 40 years of shoreline change at Daytona Beach is shown in Figure 3 to illustrate some of the features of the model. In the background, the equilibrium shoreline position is plotted in yellow, while the blue line in the foreground represents model predictions. Both curves are plotted with at a temporal resolution of Δt = 3 hours. The equilibrium shoreline position is strongly influenced by both the high and low frequency variations in the forcing parameters, while the predicted shoreline is relatively insensitive to the high frequency variations. In order to obtain an appreciable shoreline response, either the magnitude or the duration of the forcing has to exceed some critical value. The inset plot is an enlargement of an individual year, where the variability of y_{eq} and y_{pr} reflects a typical annual cycle. As shown, the predicted shoreline generally begins the year in an eroded condition, builds out gradually during the spring and summer, then erodes again during the fall and winter. For the specific year chosen, Hurricane Diana in September 1984 results in a significant amount of predicted erosion. Between September and November a number of smaller storms continue to erode the shoreline, until finally the Thanksgiving Day Storm delivers a final knockout blow, resulting in the most eroded condition of the year. The measured shoreline data for the site are also plotted in the figure (black x's connected by a dotted line) where the agreement between the model predictions and the data for many of the points indicates that ESlMod is successful even over an extremely lengthy, 40-yr simulation.

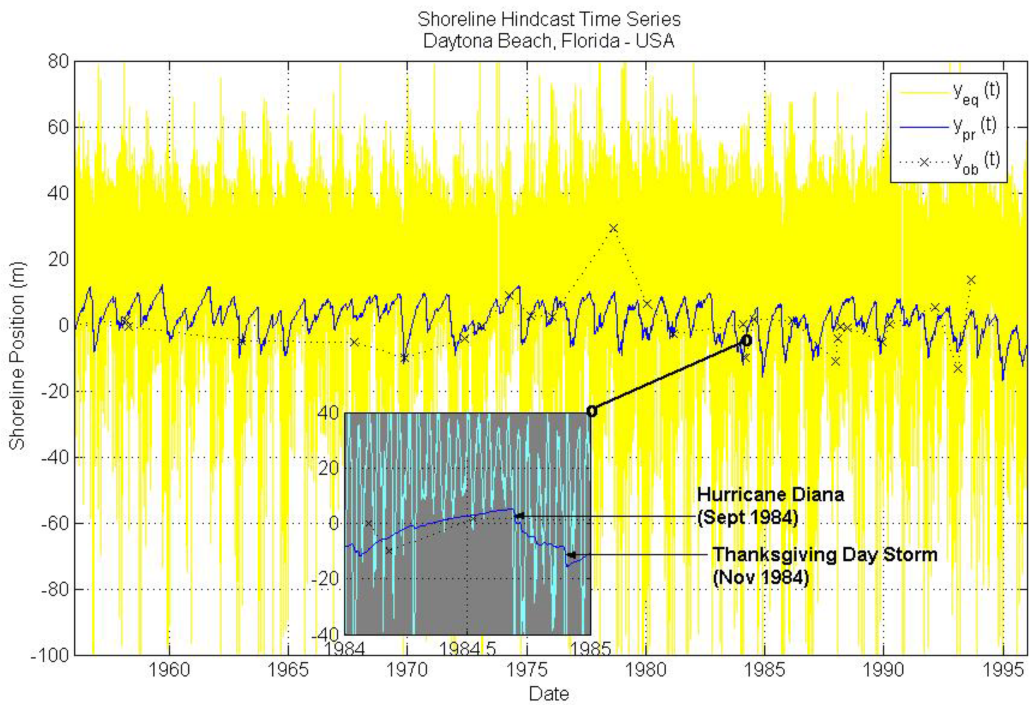

Figure 3 Detailed illustration of model behavior at Daytona Beach, Fl.

4.1 Wildwood, NJ

As described previously, ESlMod was run for each possible parameter combination resulting in a total of 225 (15x15) simulations at each site. The results of two of these simulations at Wildwood, NJ are plotted in Figure 4, along with the historical shoreline record. The measurements are represented by the black line, while the best simulations based on the lowest NMSE (0.441) and maximum CAP (0.686) score are depicted by the red and blue lines respectively. What appear to be grey error bars in the background are actually markers indicating the range of predictions for a given data point. For example, all of the predictions for the last data point lie between y = +4 m and y = +20 m. No outliers were removed prior to plotting the data so that the envelope defined by the grey bars includes both the best and worst predictions. The parameter combination that results in the prediction with the lowest NMSE at Wildwood is $\{k_a=f(H_b^{-2}), k_e=f(H_o/L_o)\}$. Overall, the model does a good job of reproducing the observed shoreline changes at Wildwood, including the significant erosion that occurred between 1991 and 1992. These results are obtained in spite of several factors – the removal of a substantial long-term trend, intermittent tidal data, and the distance from the site to the offshore buoy – which make accurate predictions of the shoreline variability at Wildwood a challenge.

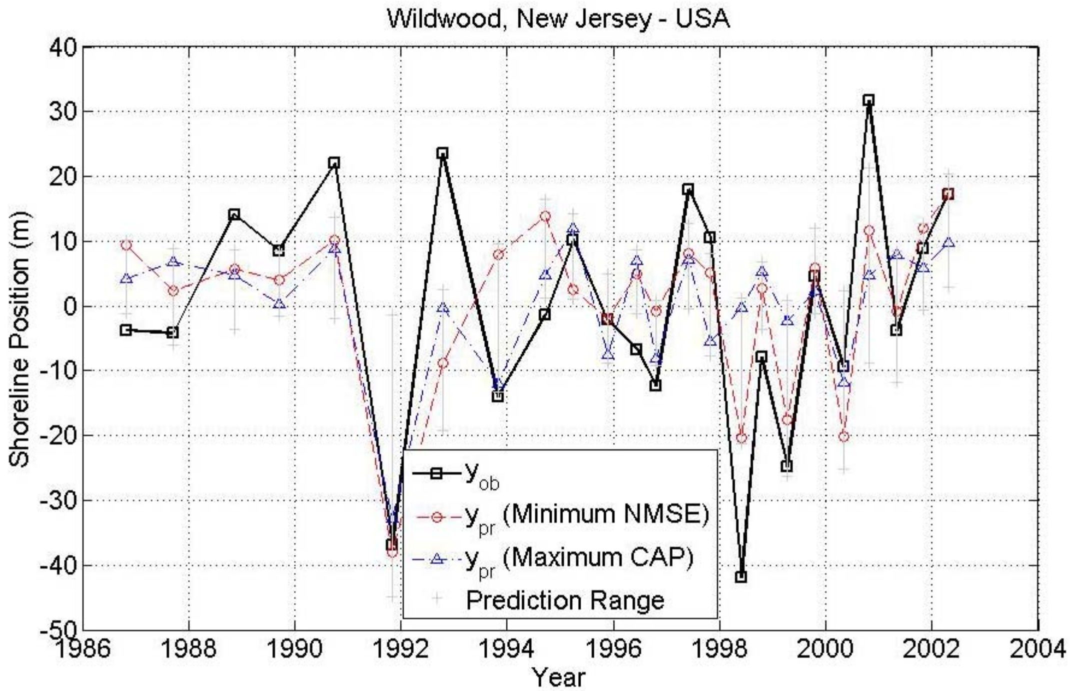

Figure 4 Comparison of hindcast and measured shorelines at Wildwood, NJ.

4.2 Torrey Pines, CA

The results from Torrey Pines are plotted in Figure 5, where the line colors/styles are consistent with those used in the previous figure. Compared to the results at Wildwood, the predictions for Torrey Pines are slightly better based on the NMSE (0.303) and about the same based upon the CAP (0.686) score. The major difference between the predictions at Torrey Pines and those from Wildwood are that the Torrey Pines predictions represent a much shorter time span. While the Wildwood data were collected over a period of 16 years on an approximately semi-annual basis, the Torrey Pines data were collected monthly over a period of 2 years. Unlike Wildwood where the envelope defined in grey was relatively narrow, the range of predictions obtained at Torrey Pines suggests that certain parameters are clearly better than others. Based on the results shown in Figures 4 and 5, it appears that ESlMod is slightly more adept at predicting large scale, medium to low frequency shoreline variations than the monthly changes measured at Torrey Pines. Considering the age of the data set, the lack of measured wave data for the site, and the intermittency of the local tide gauge, these results are considered adequate.

Blindfold tests were also performed at Torrey Pines, where the first half of the data was used to calibrate the model, and the second half was predicted. An example is shown in Figure 6, where a dashed line is used to separate the calibration and prediction regions. On average, the NMSE associated with the blindfold test increases by 44% compared to the original simulations. The distribution of this 44% varies, as some parameter combinations require more calibration data than others. The magnitude of the increase in the NMSE is not too surprising considering the fact that the blindfold calibrations are based on a total of only 11 data points.

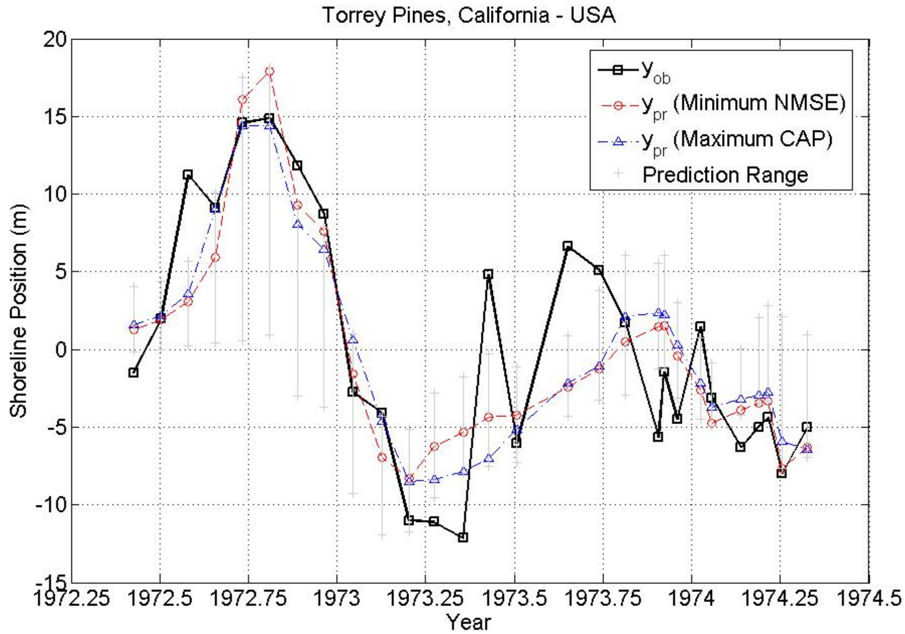

Figure 5 Comparison of hindcast and measured shorelines at Torrey Pines, CA.

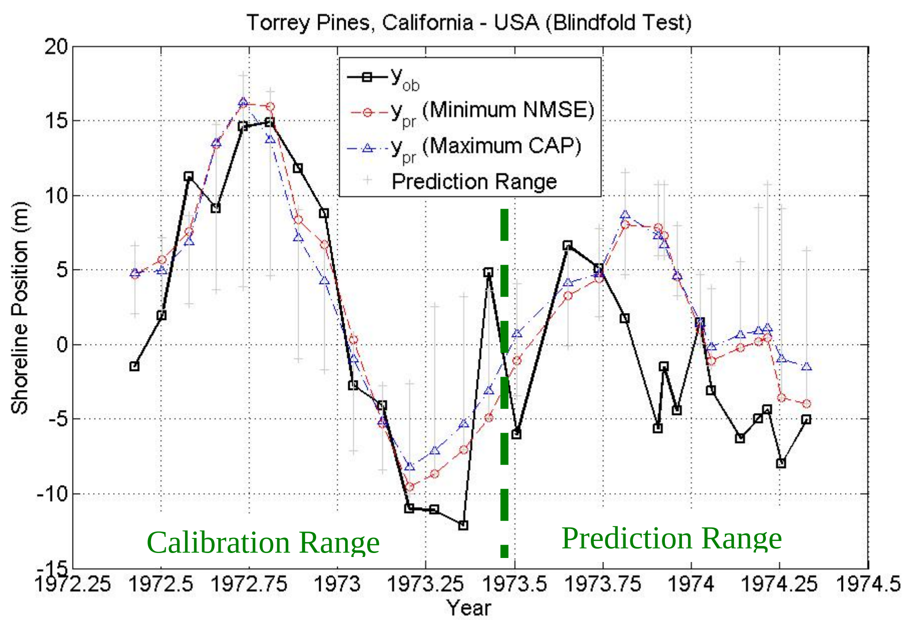

Figure 6 Blindfold test of ESlMod performed on the Torrey Pines, CA data set. Observations to the left of the dashed line were used to calibrate the model and predict the remaining data.

4.3 Long Beach, WA

In general, the most accurate simulations were obtained using the Long Beach data set. The predictions shown in Figure 7 are a prime example, where the NMSE associated with the simulation shown in red is 0.254, and the CAP score associated with the simulation shown in blue is 0.911. The predictions plotted in the figure represent just two of a set of excellent predictions. The envelope of predictions shown in the figure illustrates just how good and how consistent the model simulations are at Long Beach. Compared to the previously discussed sites, the Long Beach location has several advantages which lead to the excellent predictions. The nature of the shoreline itself at Long Beach, consisting of a long, straight, uninterrupted coastline, which tends to undergo significant, generally longshore uniform changes makes it ideal for testing a cross-shore model. In addition, the forcing data at the site is far superior to that at each of the other two sites. Both wave and tide data are available from nearby gauges, which were extremely reliable for the duration of the simulations.

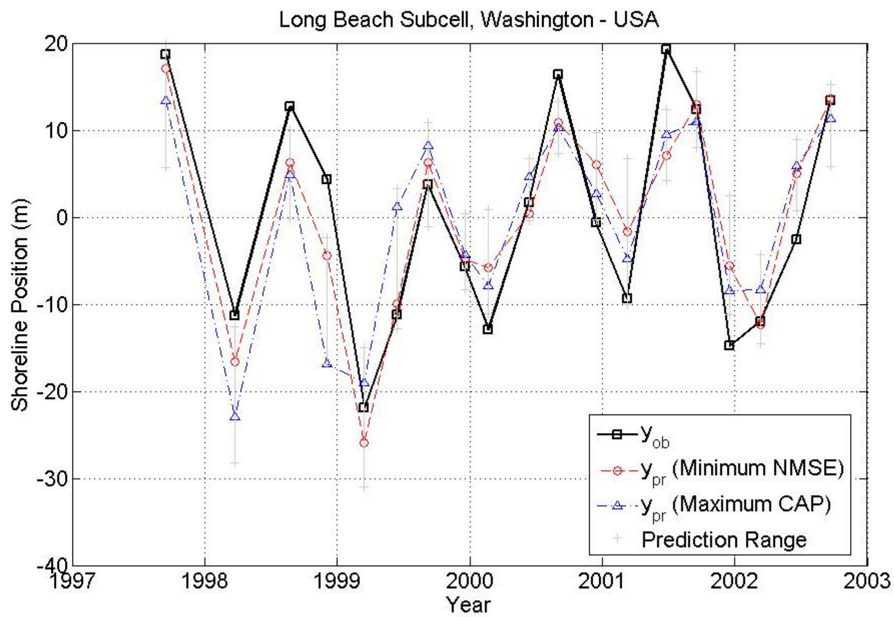

Figure 7 Comparison of hindcast and measured shorelines at Long Beach, WA.

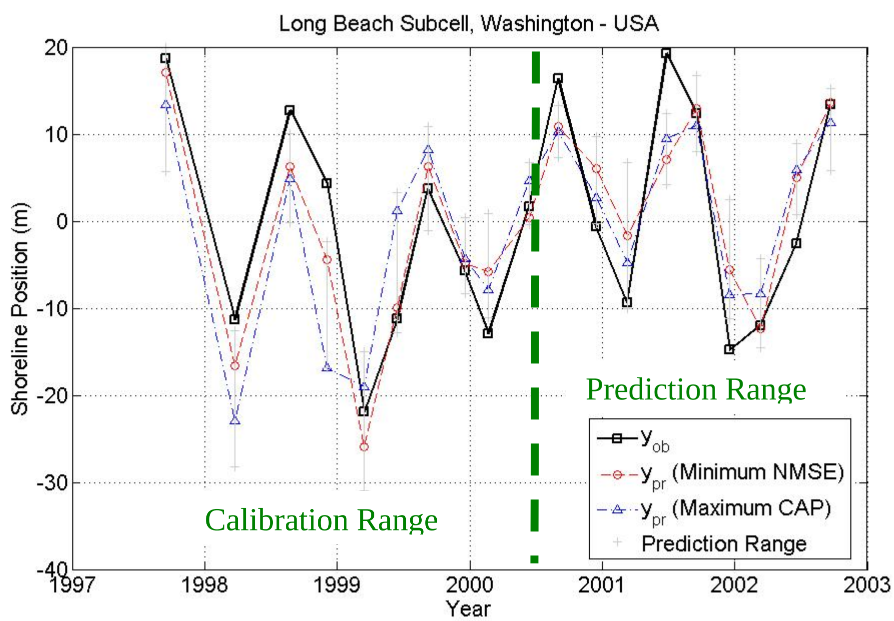

Figure 8 Blindfold test of ESlMod performed on the Long Beach, WA data set. Observations to the left of the dashed line were used to calibrate the model and predict the remaining data.

Blindfold simulations were also performed at Long Beach as shown in Figure 8. As expected, the average NMSE associated with these simulations increases, however somewhat less (23%) than might have been expected considering that the blindfold calibration is only based on a total of 8 data points. This result confirms the fact that the coefficients at Long beach are well defined, and suggests that reasonable predictions can be made using the values determined from either the 8 point or full calibration.

5. DISCUSSION

5.1 Model Performance

The average NMSE for the 2925 simulations (15 possible parameterizations for k_a and k_e at a total of 13 sites) performed during the evaluation of the current version of ESlMod was 0.653. This result includes both what appear to be appropriate as well as inappropriate parameterizations. If only the best simulations from each site, theoretically representing only the most appropriate parameterizations of the rate coefficients are considered, the average NMSE drops to 0.476. Given the diversity of the data against which these calibrations and evaluations are performed, these results are considered promising.

Blindfold tests performed on the Torrey Pines and Long Beach data sets, showed that on average the NMSEs increase by 49% at Torrey Pines and 23% at Long Branch. The distribution of these increases varies depending on the parameter combination (i.e. the error associated with one parameter combination may increase substantially, while that associated with another may only increase a small amount). In general, the values of the coefficients associated with the erosion parameter appear to be more stable, changing on average only 25% with respect to the value based on the full calibration, while the corresponding average change in the accretion coefficients is 62%.

5.2 "Best" Rate Parameters

As discussed in Section 3, a total of 225 simulations were performed at each site, representing all possible combinations of the 15 parameters for k_a and k_e. Two different methods were used to identify the most appropriate parameterizations of each coefficient. The first, and perhaps most direct way is to simply select the parameters that result in the lowest NMSE (best simulation) at each site. Using this methodology, the best parameterization of k_a is given by either $H_b^{2.5}$, $H_b^{-2.5}$, or P^{-1} (3 sites each), while the best parameterizations of k_e are given by $H_b^{2.5}$ (5 sites) and H_o/L_o (3 sites). A second approach is to average the performance of the model for each specific form of one coefficient across all fifteen forms of the other. This method is slightly more robust in that the parameters selected in this way are completely independent of one another. Using the second method, both $H_b^{2.5}$ (3 sites) and $H_b^{-2.5}$ (4 sites) are shown to provide good parameterizations of k_a, while the same two parameterizations ($H_b^{2.5}$- 5 sites and H_o/L_o- 3 sites) are obtained for k_e.

5.3 Coefficient Variability

If ESlMod is to eventually be used for prediction, particularly at sites without a significant shoreline monitoring program in place, it is desired that the calibration coefficients fall within a relatively narrow range, such that with some background knowledge of the site characteristics an appropriate value for the coefficients can be chosen. Each form of the rate parameter has a related calibration coefficient, and a series of histograms (30 in total) were prepared to graphically show the variation in the values obtained for the various simulations across all 13 sites. As shown in Figure 9 typically the variability is substantial. When the data are grouped regionally however, such that only sites with similar characteristics are plotted together, the variability is reduced significantly as shown in Figure 10. This result is typical of what happens for all the coefficients, and suggests that while the various parameterizations incorporate some measure of the regional variability, none of them capture all of it. Conveniently, the “most appropriate” parameters discussed in Section 5.2, are typically among the most stable, exhibiting only minimal variations within each region.

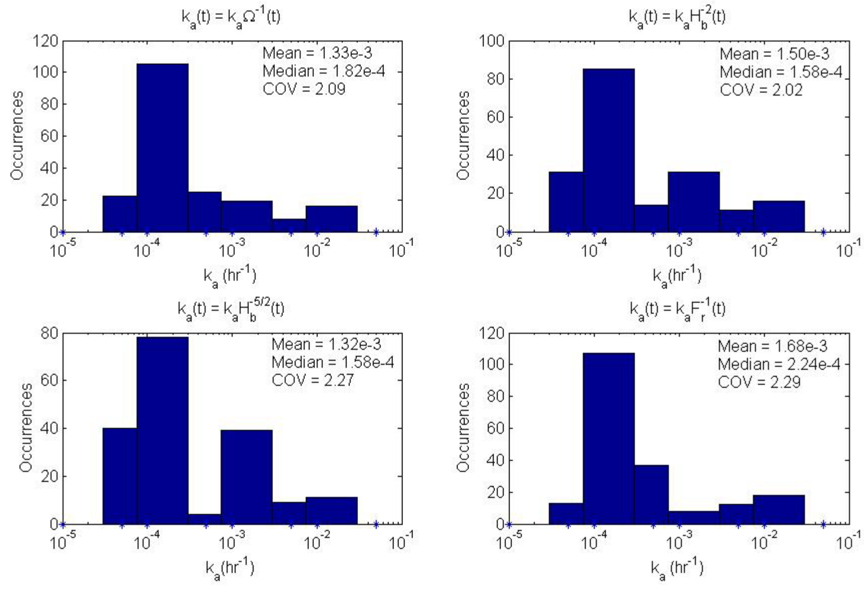

Figure 9 Histogram illustrating the typical variability associated with the coefficients for the indicated forms of the rate parameter.

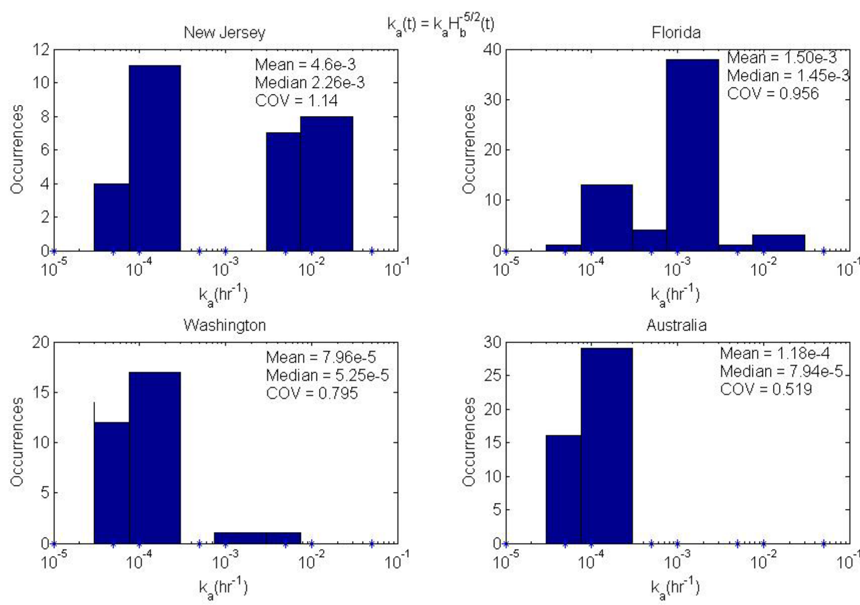

Figure 10 Histograms illustrating the substantial reduction in the variability of the coefficient associated with $k_a = k_aH_b^{-5/2}(t)$ when the data are grouped regionally.

5.4 Response Characteristics

In its simplest form (i.e. with k_α taken as a constant), eq. 1 can be idealized as a simple linear filter with an associated amplitude and phase response function given by

$$|F(\omega, k_\alpha)| = \frac{1}{\sqrt{1+\omega^2\left(\frac{1}{k_\alpha}\right)^2}} \tag{5}$$

and

$$\phi(\omega, k_\alpha) = \tan^{-1}\left(\frac{\omega}{k_\alpha}\right) \tag{6}$$

respectively. These results suggest that, the response y(t) will be lagged and damped with respect to the forcing $y_{eq}(t)$ by a degree dependent upon the relationship between the rate coefficient k_α and the frequency of the forcing, ω. Figures 11 and 12 illustrate this relationship graphically. For example in order for a semi-diurnal tide ($\omega \approx 1/12$ hrs) to generate a significant shoreline response, a rate coefficient greater than 0.1 hr^{-1} is required.

The average values of k_a and k_e, for the parameterization k_α = constant are shown on Figures 11 and 12. If a significant amplitude response is defined as $|F(\omega,k_\alpha)| = 0.5$, Figure 11 indicates the approximate timescale associated with erosion in the model is on the order of a week, while the timescale associated with accretion is several months. Both timescales seem excessive; however keep in mind that the parameterization k_α = constant was not found to be particularly good, and perhaps represents a vast oversimplification of the problem. Nonetheless, the relationship between the two time scales reflects the natural condition, where the erosion timescale is much shorter than that of accretion.

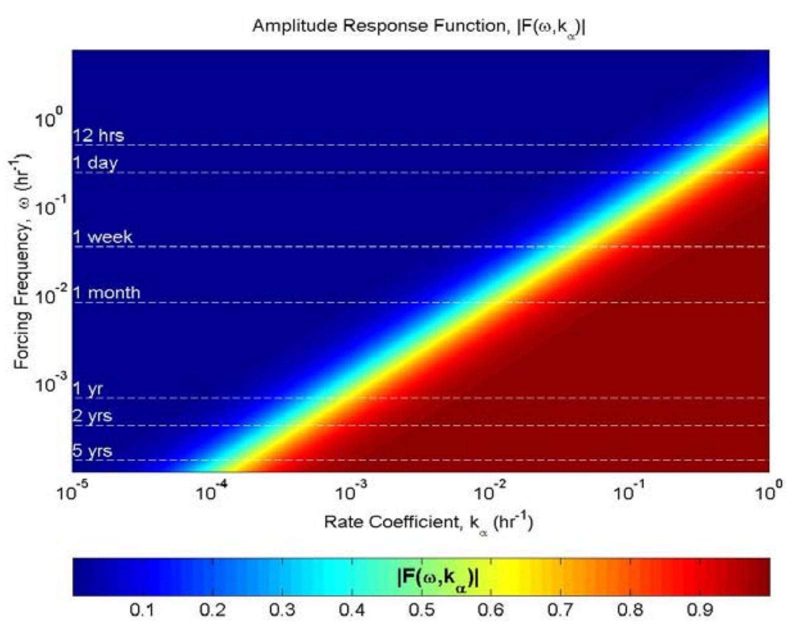

Figure 11 Amplitude response function, $|F(\omega,k_\alpha)|$.

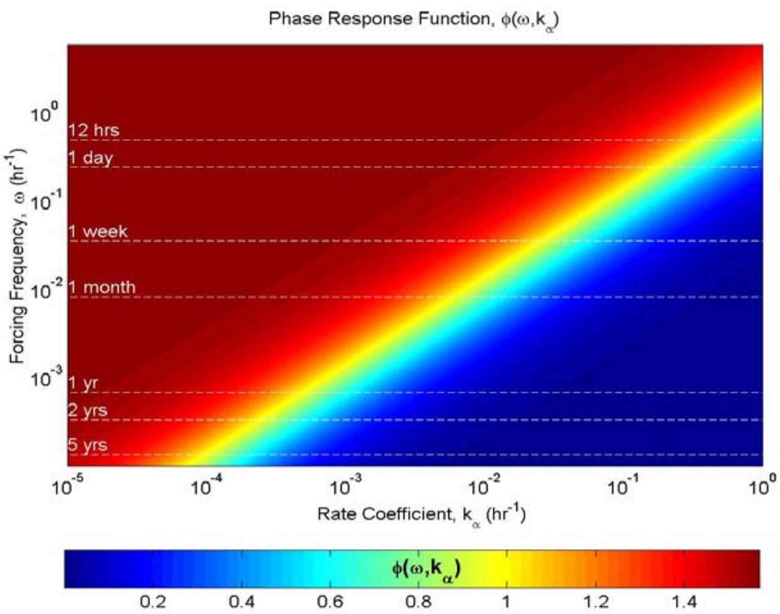

Figure 12 Phase response function, $|F(\omega,k_\alpha)|$.

6. CONCLUSIONS & FUTURE WORK

The Engineering Scale Shoreline Model represents a potentially useful new technique for simulating shoreline changes over longer timescales. ESlMod predicts the shoreline response due to variations in waves and water levels using a simple equilibrium equation approach, where the rate of shoreline response at any given time is proportional to the degree of disequilibrium. Conservation of volume arguments are used to derive an equation for the equilibrium shoreline position in terms of the breaking wave height and local water level. The constant of proportionality in the governing equation can be interpreted as a rate coefficient, which can either be determined through calibration or parameterized in terms of the local conditions. Compared to previous generations of the model, the present version of ESlMod contains several improvements, designed to more realistically represent some of the physical processes involved. The most significant modification was the incorporation of a larger number of physically based rate parameters and the consideration of the inverses of these parameters. A total of 15 rate parameters were considered for both erosion and accretion, resulting in 225 possible parameter combinations. Other less important changes include a slight modification to the way in which y_{eq} is calculated, the inclusion of a time varying beach slope, and modifications to the calibration and computational routines.

Overall, the model has been evaluated and calibrated at a total of 13 sites in the United States and Australia, with generally good results. An average normalized mean square error of 0.653 was obtained. This result represents the average calculated over all simulations including those for which the rate coefficient parameterizations appear less appropriate; however if only the most appropriate (based on the lowest NMSE) parameterizations for each site are included in the average, the mean NMSE reduces to 0.476. The "most appropriate" or "best" rate parameters were selected using two different methods. If the coefficients corresponding to the lowest NMSE at each site are used to select the most appropriate parameterizations, $H_b^{2.5}$, $H_b^{-2.5}$, and P^{-1} provide the best parameterization of the accretion coefficient, while $H_b^{2.5}$ and H_o/L_o give the best parameterization of the erosion coefficient. If instead, the lowest average NMSE for each parameter (across all 15 forms of the other parameter) is used as the criterion, $H_b^{2.5}$ and $H_b^{-2.5}$ appear more appropriate for k_a, while the same parameterizations ($H_b^{2.5}$ and H_o/L_o) are obtained for k_e.

If the model is to be applied in a predictive sense, particularly at a site with limited historical data, the variability of the coefficients associated with the rate parameters is extremely important. Ideally the range of values would be small such that in the absence of historical data, an appropriate value could be selected, and the model applied without calibration. The results presented here indicate that while the variability of the coefficients is extremely large across the thirteen sites, when the data sets are grouped according to region, the variability is reduced significantly. Most importantly, the parameters identified as being most appropriate generally exhibit the least variation.

As a first step towards applying the model in a predictive sense, blindfold tests were performed on both the Torrey Pines, CA and Long Beach, WA, data sets. For the blindfold tests, the first half of the data was used to calibrate the model, while the second half was used to evaluate the predictions. The average percent increase in the NMSE of the predictions at Long Beach and Torrey Pines, compared to the original hindcasts in which the calibration and evaluation were performed simultaneously using the full data set was 23% and 49%, respectively. This is considered reasonable considering, the limited amount of data (14 points at Torrey Pines, and 8 at Long Beach) upon which the blindfold calibrations are based.

The response characteristics of the model were analyzed by considering an analogy between a simplified version of ESlMod and a linear filter. Analytic expressions were obtained for the amplitude and phase response as a function of the input forcing and a constant rate coefficient. The results showed that consistent with nature the response timescale of erosion was much greater than that of accretion; however the values obtained for both were larger than expected (on the order of weeks for erosion and months for accretion). Given the fact that the analogy represents a substantially simplified version of ESlMod, and that the simulations using constant rate coefficients do not produce particularly good results, the relationship between the response timescales and not the timescale itself, is considered the most important information obtained from this analysis.

Work on the model is progressing along several fronts. Current plans call for integrating ESlMod with wave and water level forecasts currently being produced at Stevens. An example of such a forecast during the passage of Tropical Storm Ernesto is shown in Figure 13. It is hoped that the model will eventually be incorporated into the Stevens real-time observational and short-term forecasts which are currently in production and publicly available over the internet (http://www.stevens.edu/maritimeforecast). At the same time work has begun on a simple longshore model (one-line in nature) which will ultimately be coupled to ESlMod. The complete model will represent one of the first models applicable over engineering time-scales which takes into account both longshore and cross-shore processes, while preserving the computational efficiency essential for long-term simulations. A long-range goal is to be able to use the combined model to make long-term forecasts using Monte Carlo techniques, which will be able to synthesize a variety of different scenarios due to the efficiency of the model.

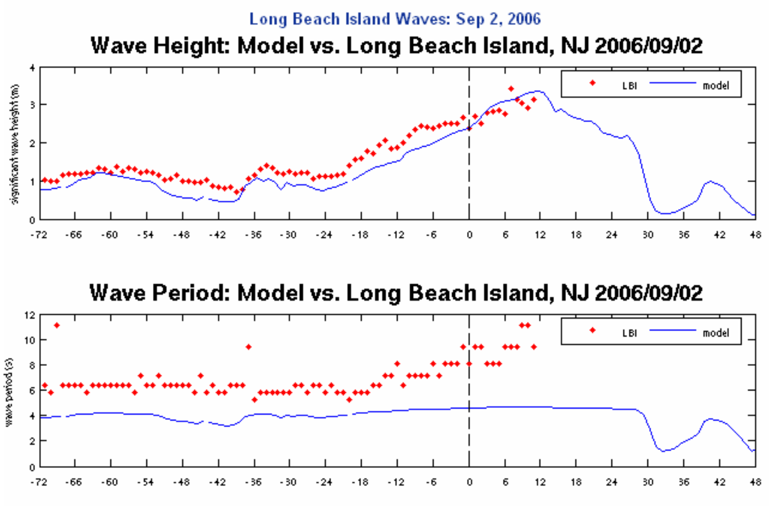

Figure 13 Screen capture of the wave forecast for September 2, 2006 during the passage (over land) of Tropical Storm Ernesto for Long Beach Island, NJ. In the upper panel, the measured and predicted H_s are plotted, while in the lower panel the measured T_p and predicted T_{avg} are plotted.

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